Simulation of Groundwater level by Artificial Neural Networks of Parts of Yamuna River Basin

Saad Asghar Moeeni, Mohammad Sharif, Naved Ahsan, and Asif Iqbal

1 Introduction

Groundwater is the most important source of natural resources. It is a vital source of industries, agriculture, and domestic requirements which want to be carefully managed for hard rock and drought-prone areas [1]. It has become a reliable source of water in all climatic regions of the world [2]. Groundwater is the largest available freshwater resource in the whole world. Aquifer wells provide potable water to 50% of the world's population and record 43% of overall irrigation water consumption. In addition, worldwide 2.5 billion citizens depend entirely on groundwater supplies in order to meet their everyday needs [3]. In arid and semi-arid climates, with frequent dry spells and sometimes erratic surface waters (Liamasand Martínez-Santos, 2005), groundwater is significant. Groundwater is an important medium of water supply in different regions of the world, as a result, several studies highlighted different features of groundwater such as storage potential, hydrogeology, water quality , exposure, and so on [4–7]. Furthermore, groundwater simulation has become an essential tool among scientists and engineers working on water management for optimizing and protecting the development of groundwater. Physically, during the past few years, simulations have been implemented to simulate and analyze the groundwater environment and then take remedial steps in order to allow effective use of the control of water supplies. These models act as a hydrological variableness framework and

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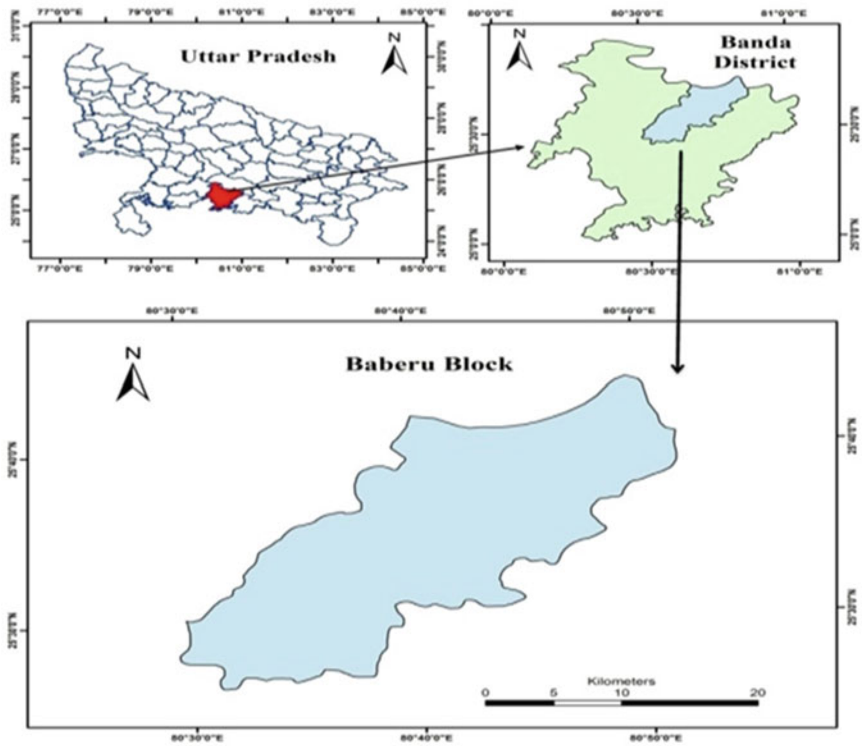
understand the physical processes within the aquifer. Hydrologists, mechanics, and environmental engineers use this frequently in computer applications but challenges range from aquifer protection yield to soil quality and clean-up. Although such models use data in highly intense, laborious, and expensive ways. As a consequence, physical models in developed countries are significantly limited because of the lack of appropriate and high-quality data.

In this paper, we have used ANN for groundwater prediction of four Blocks of the BANDA District of UP. Prediction of groundwater is very important for planning groundwater administration and water resources in any river basin. Physical-based models are widely used in groundwater simulation. Wide numbers of numerical models have already been developed for different areas with different objectives such as to express provincial groundwater behavior and to understand local hydrological processes [8–10]. The relevance of the ANN technique in water management ranges from event-based simulation to real-time simulation. It has been used for rainfall-runoff simulation, precipitation simulation as well as for stream flows simulation, evapotranspiration, water quality as well as groundwater [11–13]. In the literature, comparatively less research on the ANN-based approach in groundwater hydrology has been used in comparison to surface water hydrology. Neural networking practises are used in groundwater hydrology for the evaluation of the aquifer parameters [14–20], groundwater quality predictions [17, 21, 22].

2 Study Area

Banda district lies between latitude 25°00′00” and 25°59′00” north and longitude 80°06′00” and 81°00′00”. The district’s total area is 4460 km^2. Baberu is one block of the Banda district. It consists of 570.41 km^2. The area geologically comprises Precambrian Bundelkhand granites overlain by Vindhyan and quaternary alluvium. The area is roughly plain apart from some isolated granitic hillocks and the division of point bars natural levees, and flood plain. It is made up of unconsolidated deposits of Indo-Gangetic alluvium of recent age comprising silt clay, silt, Kankar, sand and their admixtures of various grades.



3 Study Period

The periods for study depend from the time of minimum to the time of maximum water table elevation as the non-monsoon period and from the time of minimum to the time of maximum water table elevation as monsoon period. For this purpose, data have been taken from 1995 to 2016 in northern India and the water year is considered from November 1 to October 31 next year. The study periods are taken as non-monsoon periods for the duration of November to May.

4 Materials and Methods

4.1 Ground Water Balance Equation

$$\boldsymbol{R_c + R_i + R_r + R_t + S_i + I_g = E_t + T_p + S_e + O_g + \Delta S} \quad (1)$$

where

R = Rainfall Recharge;

R_c = Canal seepage Recharge;

Rr = Field irrigation Recharge; Rt = Recharge from pond storage

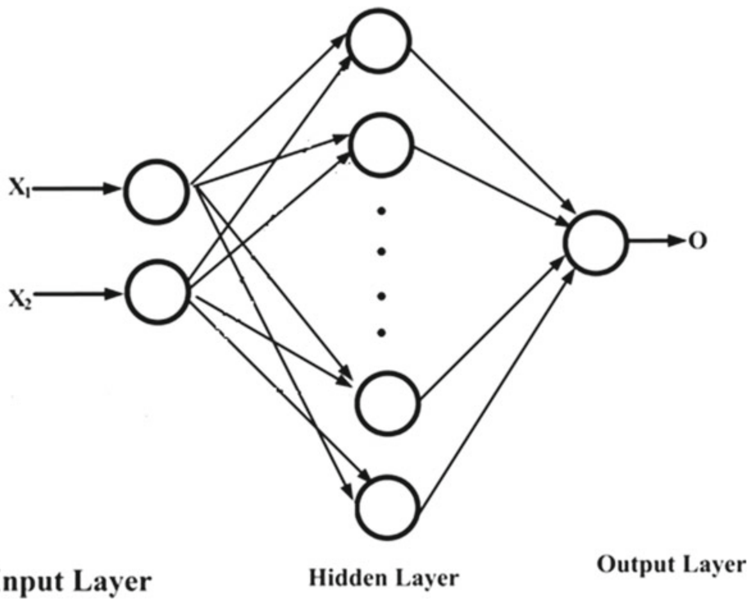
I_g = inflow from blocks; Et = Evapo-transpiration;

T_p = Groundwater discharge from tube well;

S_i, S_e = influent and effluent seepage from rivers; Og = outflow to other blocks; and

ΔS = change in groundwater storage.

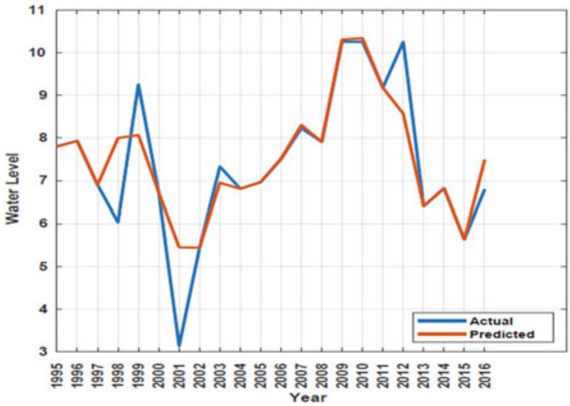
All these parameters are calculated by Central Groundwater norms [Ref].



ANN Architecture

For the prediction of groundwater resources, ANN model is proposed the proposed models have been built using MATLAB The proposed ANN model consists of only a hidden layer in between input and output layers. Transfer function used on behalf of the hidden layer is sigmoid whereas used for output layer it is linear. Four different algorithms Levenberg Marquardt, Gradient Descent, Scaled Conjugate Gradient, and Bayesian Regularization backpropagation algorithm are used for training. The proposed model has been trained, tested, and validated with recharge and discharge and groundwater level data. The block diagram of the proposed two inputs and one output ANN model is shown in Fig. 1. The structure of an ANN is usually prejudiced by the nervous structure of humans.

Fig. 1 Actual and predicted groundwater level through Levenberg–Marquardt for Non-Monsoon season



4.2 Levenberg–Marquardt (LM)

The Levenberg–Marquardt technique is a modification of the typical Newton algorithm for ruling an optimum answer to minimize complexity. It employs approximation to the Hessian matrix in the subsequent Newton-like weight update

$$x_{k+1} = x_k - \left[J^T J + \mu I\right]^{-1} J^T e \tag{2}$$

when neural network x is the weights, J of Jacobian matrix minimizes the presentation criterion, μ of a scalar emphasizes the phase of learning, and e is the vector of the residual error. When μ is bigger, Eq. 1 is decent in the gradient for a limited stage scale. The Newton method is faster and more reliable, near to minimum error, because the objective is to change size. The scalar μ is zeros equation 1 automatically is the Newton method. Newton's method is quick and more accurate because of the shifting toward the Newton method quickly. Levenberg–Marquardt has computational requirements so it can be used for small networks [23].

4.3 Bayesian Regularization (BR)

The Bayesian regularization is an algorithm that mechanically sets optimum standards in support of the parameter of the point function. The weight and bias of the network be understood to be a random variable with specified circulation. The benefit of Bayesian control is that the feature should not surpass the scale of the network. The effective usage of Bayesian regularization in literature [24].

4.4 Gradient Descent by Means of Momentum and Adaptive Learning Rate Back Propagation (GDX)

In order to measure the derivative of the output cost function according to the arbitrary weights and bias of the network, this technique utilizes a standard back propagation algorithm. This strategy utilizes gradient descent with momentum to control each variable. With each level of shift, the learning rate is increased if efficiency declines, one of the simplest and most popular ways to train a network [25].

4.5 Scaled Conjugate Gradient (SCG)

The scaled conjugate gradient (SCG) algorithm [26] determines the quadratic error calculation in the neighborhood. Moller [26] proved this hypothetical base work to be the primary order approach for the primary derivative, such as regular back propagation, and found an important way to obtain a local minimum of second-order technique in the second derivatives. SCG is a second-order combination of gradient algorithms that has helped to reduce a multidimensional target function. SCG is a simple algorithm and employs a scaling method that holds the search through information iteration away from the time-consuming line [26, 27] has shown that the SCG approach presents super linear convergence for major problems.

4.6 Criteria for Evaluation

The following statistical indices such as R^2 efficiency criteria, root mean square error (RMSE), Mean Absolute Error (MAE), Mean Square Error (MSE), and coefficient of correlation (r) were used to evaluate the performance.

5 Results and Discussion

In Babeu Block of BANDA, part of the Yamuna river basin, the purpose of ANN is to measure the capacity to predict a fluctuation of the groundwater level. The network has the following input parameters, Recharge and Discharge. In recharge all the parameters are included like recharge from rainfall, recharge from canal seepage, recharge from field irrigation, recharge from pond storage and in discharge all the parameters are included like groundwater discharge from tube well, influent and effluent seepage from rivers, and for the output parameters, groundwater levels were taken. The four wells' groundwater levels were estimated by using the feed-forward network with a back propagation algorithm. Minimum errors were saved in the trained networks. The neural networks of each wells producing maximum value for R^2. was selected as the best network.

For ALIHA well LAT = 25.495 LONG = 80.525

Year	Recharge in Ham	Discharge in Ham	Groundwater level in MBGL
1995	2776.139	74.557	6.53
1996	2594.47	74.63	5.09
1997	2488.79	71.615	5.1
1998	2903.234	71.610	5.28
1999	2352.035	80.709	5.33
2000	3168.478	80.704	7.43
2001	3436.0.904	80.700	4.08
2002	3435.626	80.695	5.73
2003	3137.422	80.535	1.83
2004	4802.41	81.270	5.23
2005	1735.716	81.717	5.3
2006	3301.524	82.368	5.91
2007	2686.633	82.156	5.5
2008	3983.97	82.704	6.09
2009	3155.92	83.233	8.03
2010	3077.607	83.802	7.02
2011	3556.657	109.231	6.05
2012	3294.387	109.784	8.02
2013	3152.837	111.968	6.11
2014	2603.938	113.001	6.5
2015	3019.837	114.034	6.8
2016	3593.046	114.146	8.3

HAM = Hectare Metre, MBGL = Metre Below Groundlevel

For Mural well LAT = 25.51, LONG = 80.562

Year	Recharge in HAM	Discharge in HAM	Groundwater level in MBGL
1995	7082.457428	190.2115222	4.3
1996	6618.994941	190.410659	3.9
1997	6349.392655	182.7041859	2.1
1998	7406.700558	182.6928576	4.7
1999	6000.488148	205.9046163	3.1
2000	8083.388163	205.8932881	2.42
2001	8768.194147	205.8819598	2.6
2002	8764.93384	205.8706316	9.65

(continued)

(continued)

Year	Recharge in HAM	Discharge in HAM	Groundwater level in MBGL
2003	8004.157891	205.4621211	0
2004	12,251.87134	207.3352643	1.33
2005	4428.140221	208.4777991	2.87
2006	8422.813025	210.1386775	8.52
2007	6854.111735	209.5955874	5.97
2008	10,163.88281	210.9957958	5.95
2009	8051.360821	212.3960043	5.36
2010	7851.559325	213.7962128	6.3
2011	9073.706649	278.6707427	6.13
2012	8404.605956	280.0800508	3.6
2013	8043.484473	285.6519149	2.34
2014	6643.138717	288.287559	3.31
2015	7704.17571	290.923203	5.33
2016	9166.541755	291.2091086	2.26

For Patwan well LAT = 25.59 LONG = 80.56

Year	Recharge in HAM	Discharge in HAM	Groundwater level in MBGL
1995	13,691.21989	367.7011551	4.3
1996	12,795.29261	368.0861097	7.2
1997	12,274.11981	353.1885944	6.5
1998	14,318.01985	353.1666955	7.9
1999	11,599.64652	398.0377444	6.3
2000	15,626.13626	398.0158455	6.52
2001	16,949.94645	397.9939467	7.87
2002	16,943.64389	397.9720479	8.74
2003	15,472.97486	397.1823492	0
2004	23,684.30256	400.8033545	7.93
2005	8560.113787	403.012008	11.66
2006	16,282.28428	406.2226805	11.05
2007	13,249.80092	405.1728238	16.6
2008	19,647.97613	407.8795908	17.35
2009	15,564.22365	410.5863577	17.52
2010	15,177.98396	413.2931247	17.5
2011	17,540.5379	538.7031909	14.8
2012	16,247.08788	541.4275485	11.3
2013	15,548.99775	552.1986145	5.67

(continued)

(continued)

Year	Recharge in HAM	Discharge in HAM	Groundwater level in MBGL
2014	12,841.96536	557.2936233	10.25
2015	14,893.07416	562.3886321	15.55
2016	17,719.99904	562.9413209	13.65

For Baberu well LAT = 25.54 LONG = 80.71

Year	Recharge in HAM	Discharge in HAM	Groundwater level in MBGL
1995	4581.922195	123.0553666	3.15
1996	4282.089958	123.1841961	1.95
1997	4107.673562	118.1985734	2.5
1998	4791.687917	118.1912447	2.05
1999	3881.953419	133.2078507	2.15
2000	5229.463927	133.200522	2.89
2001	5672.492038	133.1931933	2.65
2002	5670.382817	133.1858646	1.85
2003	5178.206727	132.921583	1.45
2004	7926.220778	134.1333936	1.95
2005	2864.739275	134.8725445	3.46
2006	5449.051313	135.9470325	5.62
2007	4434.196323	135.595686	5.2
2008	6575.418306	136.5015363	6.37
2009	5208.744171	137.4073867	5.5
2010	5079.484671	138.313237	5.25
2011	5870.140175	180.2831396	2.75
2012	5437.272439	181.1948768	3.65
2013	5203.64865	184.7995363	2.84
2014	4297.709523	186.5046389	3.93
2015	4984.136373	188.2097414	4.45
2016	5930.198882	188.394705	4.32

For ALIHA Well, all recharge and discharge data were calculated according to the groundwater estimation committee norms. In the year 2002, recharges were the most, i.e., 3435.626 and the discharges were the most in the year 114.146. For Murwal well, maximum recharge was found in the year 2008, that is, 10,163.88281 HAM and maximum discharge was found in the year 2016 that is 291.2091086 HAM. For Patwan well, maximum recharge was found in the year 2004, that is, 23,684.30256 HAM and maximum discharge was found in the year 2016, that is, 562.9413209 HAM. For Baberu well, maximum discharge was found in the year 2016, that is, 188.394705. HAM and maximum recharge were found in the year 2004 that is 7926.220778 HAM.

For ALIHA Well

See Figs. 1, 2, 3 and 4.

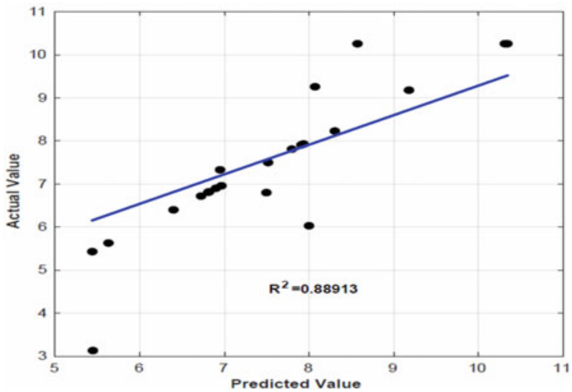


Fig. 2 Scatter diagram for actual and predicted groundwater level for $R^2 = 0.88$ for testing

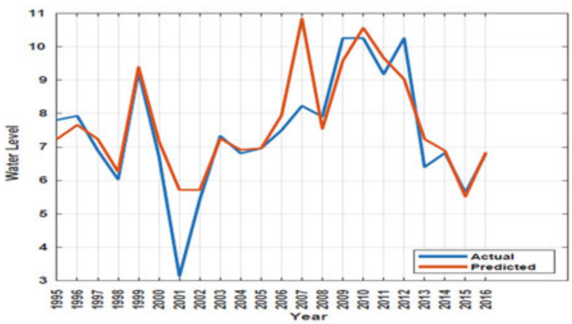


Fig. 3 Actual and predicted groundwater level through Bayesian Regularization for Non-Monsoon season

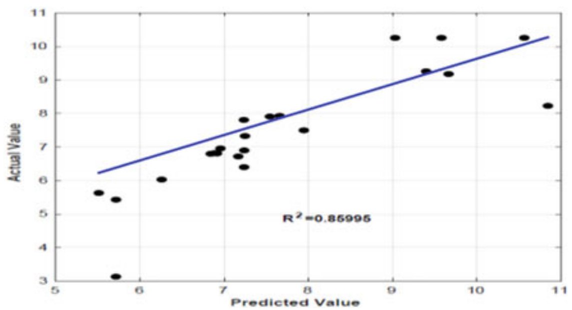


Fig. 4 Scatter diagram for actual and predicted groundwater level for $R^2 = 0.85$ for testing

For Baberu well

See Figs. 5 and 6.

For Murwal Well

See Figs. 7 and 8.

For Patwan Well

See Figs. 9 and 10.

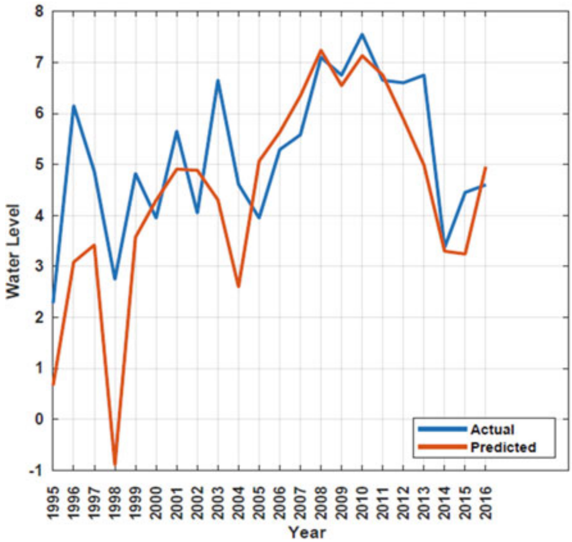


Fig. 5 Actual and Predicted groundwater level through Bayesian Regularization for Non-Monsoon season

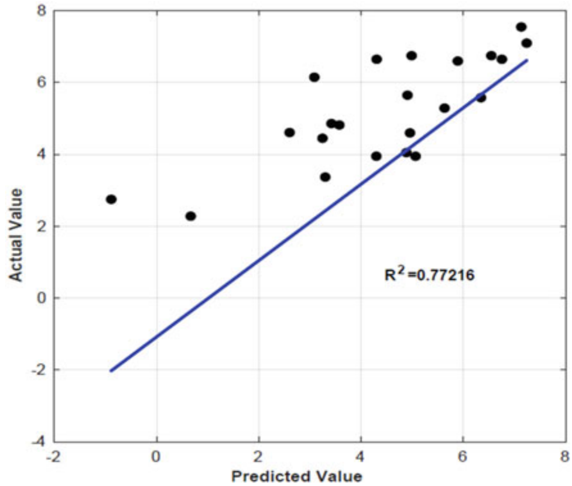


Fig. 6 Scatter diagram for actual and predicted groundwater level for $R^2 = 0.77$ for testing

Fig. 7 Actual and predicted groundwater level through Levenberg- Marquardt for Non-Monsoon season

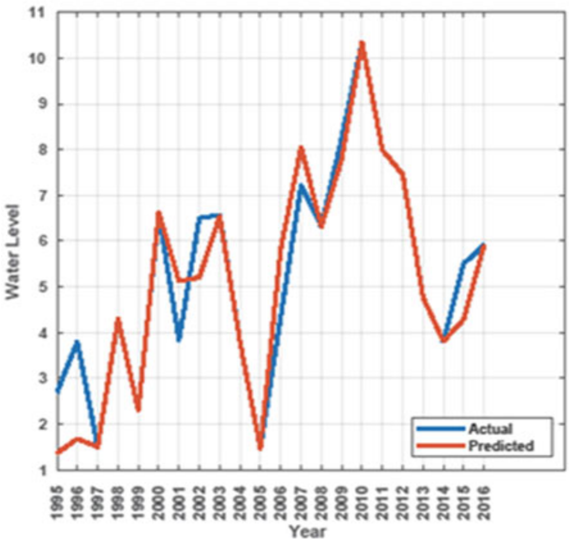
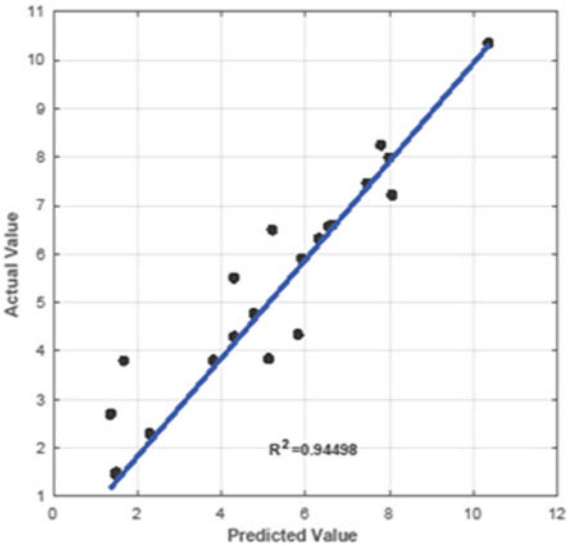


Fig. 8 Scatter diagram for actual and predicted groundwater level for $R^2 = 0.94$ for testing



6 Conclusion

The function of the artificial neural network of feed-forward back propagation into groundwater prediction has been investigated in this research paper. Input and output data are grouped into hydro-geological well classes and the LM, SCG, BR and GD have been trained for each well sheet. The findings demonstrate explicitly that the

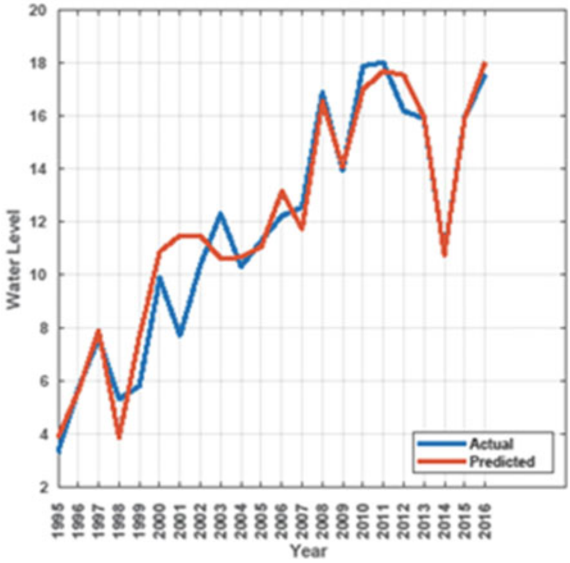


Fig. 9 Actual and predicted groundwater level through Levenberg-–Marquardt for Non-Monsoon season

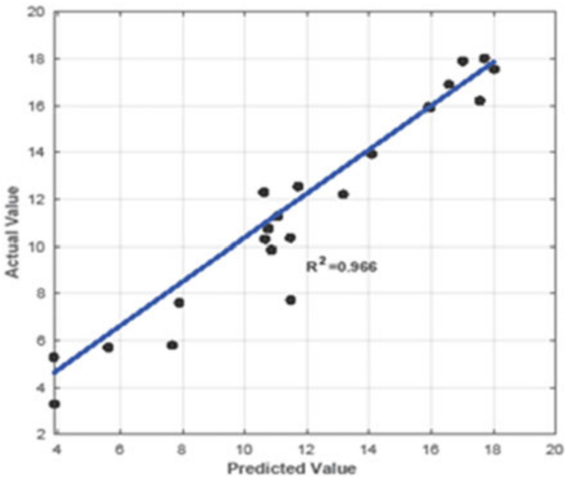


Fig. 10 Scatter diagram for actual and predicted groundwater level for $R^2 = 0.96$ for testing

LM algorithm works well for all four wells. Results demonstrate that the ANN model is capable of predicting the virtual physical structure's complex response. A major advantage of this ANN technique is that it can provide good predictions by means of limitations of groundwater data (Table 1).

Table 1 Comparison of performance of models developed for all wells, training, testing and validation

For Aliha well													
		LM			BR			GDX			SCG		
Evaluation criteria	Epoch	TRNG	TST	VALI	TRNG	TST	VALI	TRNG	TST	VALI	TRNG	TST	VALI
R^2	2000	0.88	0.85	0.85	0.85	0.83	0.54	0.34	0.22	0.16	0.86	0.83	0.72
MAE	2000	0.38	0.40	0.41	0.55	0.67	1.0	5.18	7.37	13.2	0.66	0.74	0.79
MSE	2000	0.64	0.79	0.77	0.80	0.90	4.29	39.31	81.27	205.9	1.24	1.18	1.73
RMSE	2000	0.80	0.89	0.81	0.89	0.95	2.07	6.27	9.01	14.3	1.17	1.08	1.31
For Murawal well													
R^2	2000	0.94	0.74	0.73	0.88	0.71	0.7	0.88	0.87	0.8	0.77	0.7	0.69
MAE	2000	0.45	0.14	0.14	0.85	1.17	1.32	0.89	0.78	1.71	2.56	1.17	1.4
MSE	2000	0.64	8.6	8.6	1.16	4.02	2.6	1.26	1.16	4.32	10.5	2.8	8.6
RMSE	2000	0.8	2.9	2.9	1.08	2.0	1.6	1.12	1.07	2.09	3.17	1.69	2.9
For Baberu well													
R^2	2000	0.82	0.78	0.73	0.77	0.78	0.70	0.57	0.51	0.34	0.72	0.67	0.63
MAE	2000	0.59	0.51	0.71	1.11	1.15	0.52	1.77	1.17	9.9	0.67	0.83	0.84
MSE	2000	0.85	0.87	0.97	2.1	2.5	1.38	6.81	2.13	14.0	0.97	1.31	1.47
RMSE	2000	0.92	0.93	0.98	1.4	1.6	1.17	2.6	1.46	11.9	0.98	1.14	1.21
For Patwan Well													
R^2	2000	0.98	0.96	0.75	0.722	0.721	0.51	0.67	0.455	0.44	0.88	0.86	0.84
MAE	2000	0.41	0.80	1.55	2.40	0.51	5.18	24.39	4.47	5.5	1.57	1.9	1.71
MSE	2000	0.89	1.36	15.9	9.39	0.87	50.3	8.8	105.7	66.3	4.2	6.62	6.1
RMSE	2000	0.94	1.16	3.9	3.06	0.93	7.09	29.78	1.46	8.14	2.0	2.57	2.4

LM = Levenberg Marquardt Algorithm, BR = Bayesian Regularization Algorithm, GDX = Gradient Discent Algorithm, SCG = Scaled Conjugate Gradient Algorithm

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